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Optimal Activation and Transmission Control in Delay Tolerant Networks[◇]

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***Abstract*—Much research has been devoted to maximize the life time of mobile ad-hoc networks. Life time has often been defined as the time elapsed until the first node is out of battery power. In the context of static networks, this could lead to disconnectivity. In contrast, Delay Tolerant Networks (DTNs) leverage the mobility of relay nodes to compensate for lack of permanent connectivity, and thus enable communication even after some nodes deplete their stored energy. One can thus consider the lifetimes of nodes as some additional parameters that can be controlled to optimize the performance of a DTN. In this paper, we consider two ways in which the energy state of a mobile can be controlled. Both listening and transmission require energy, besides each of these has a different type of effect on the network performance. Therefore we consider a joint optimization problem consisting of: i) activation, which determines when a mobile will turn on in order to receive packets, and ii) transmission control, which regulates the beaconing. The optimal solutions are shown to be of the threshold type. The findings are validated through extensive simulations.**

***Index Terms*—Optimal control, fluid models, delay tolerant networks, threshold policies**

I. Introduction

Delay Tolerant Networks (DTNs) have drawn considerable research interest recently due to their capability to deliver messages in frequently partitioned networks [1]. The key for message delivery is the underlying mobility of nodes [2]. "Store, carry and forward" kind of protocols are one of the natural routing options in DTNs. Mobile nodes rarely possess *a priori* information on the encounter pattern, thus an intuitive solution is to disseminate multiple copies of the message in the network, increasing the probability that at least one of them will reach the destination node within a given time window [2], generally known as epidemic-style forwarding. As in the spread of contagious diseases, epidemic forwarding passes the message to any node it encounters which does not have the message (uninfected node). Finally, the destination receives the message when it meets an infected node. A downside of this scheme is that the network is overloaded with messages.

In this paper, we refer to a more efficient variant of the plain epidemic routing, namely the *two hops routing protocol*. The source transmits copies of its message to all mobiles it encounters, but the latter relay the message only if they meet the destination [3]. Efficient energy consumption is one of the major concerns in battery operated mobile nodes due to limited energy budget in DTNs. Besides, significant energy is also consumed in node discovery process due to periodic *beaconing*[1]. Thus, we face a natural tradeoff: the higher the number of nodes involved, higher is the message delivery probability, while expending more energy. Moreover, nodes may even die due to energy shortage before actually participating in forwarding. This clearly points towards a need of controlled activation of nodes, making nodes available only when needed. Nodes can be made active later, e.g., using wake-up timers [4]. Previous research in the context of sensor networks has discussed the benefit of optimal activation times of deployed sensor nodes [5]. To the best of our knowledge, this is the first study of activation methodology to enhance energy saving policy in context of DTNs.

Our goal here is to obtain jointly optimal transmission and activation control policies that maximize the probability of successful delivery of the message by some time T, given the total energy budget and a bound on the activation rate of the relay nodes. We leverage fluid approximations of the system dynamics, and use tools from optimal control theory to obtain a closed-form optimal policy. As we will see later, this turns out to be a two-dimensional threshold type policy. We validate the model and the results using extensive simulations.

Related works

Control of forwarding schemes has been addressed in the DTNs literature before [6]. In [7] and its follow-up [8], the authors optimize network performance by designing message relays. In [9], the authors consider buffer constraints and derive buffer scheduling policies in order to minimize the delivery time. In [6], we have provided a general framework for the optimal control of a broad class of monotone relay strategies. The more recent paper [10] employs stochastic approximation to avoid the explicit estimation of network parameters.

Optimal activation of nodes in redundantly deployed sensor networks has been studied before in [5], [11]. A threshold-based activation policy was shown to perform close to the optimal policy for dynamic node activation in [5]. Scheduling/controlling the activity nodes to exploit energy harvesting features has been studied in [11].

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[1]A periodic signalling for node discovery prior to message reception.

Compared with the existing literature, this paper makes the following original contributions: **i)** Explicit accounting for the maximum allowed energy expenditure, the delivery probability within a given deadline, and the activation of relays; **ii)** A formulation rooted in optimization, which entails *joint* optimization of the activation control and the transmission control in order to maximize the time-constrained delivery probability. This is a non-standard dynamic optimization problem formulated with coupled controls.Once solved, interesting properties of the optimal solution and the special role of the control on the relay activation have emerged.

Due to space limitations, most proofs are omitted from the paper, but can be found in [12].

II. System model

We consider a network of $N+1$ mobile nodes, where one of them, the *source*, has a message to send to a destination node. We adopt the two hops routing relay policy, so that the source relays to mobiles which do not have the message but a relay transfers the message if and only if it meets the destination node. This relay strategy is *monotone* [6] because the number of copies of the message increases over time.

The time between contacts of any two nodes is assumed to be exponentially distributed with parameter ξ. The validity of such a model has been discussed in [3], and its accuracy has been shown for a number of mobility models (Random Walker, Random Direction, Random Waypoint). We assume that the message that is transmitted is relevant for some time T. We do not assume any feedback that allows the source or other mobiles to know whether the message has made it successfully to the destination within the allotted time T.

Each mobile sends periodically beacons to inform the source that they are in radio range. The source can transfer the message according to its forwarding policy. A relay node may already have a copy of the message: for such a node beaconing is not required, which may save considerable amount of energy. Henceforth, we assume that relays only keep beaconing until they receive a message copy from the source. However, some nodes can switch to inactive state to save energy.

Accordingly, we define the state of a tagged node as falling into three classes: **inactive**: the tagged node does not take part in any communication; **activated**: the tagged node does not have a message copy, it keeps beaconing until it receives a message copy; **infected**: a node with a message is active but it does not send beacons.

Notice that the average life time of a mobile may be considerably shorter than the bound T. This limited life time is due to constraints on the total energy consumed: two-hops routing is particularly convenient since a relay does not use much energy in transmission; however, the impact of beaconing is substantial in comparison to transmission energy. In this respect we assume that the probability that an activated mobile empties its battery at time $(t, t+\delta)$ is given by $\mu\delta U$ if it uses power $U(t)$ during that period.

A. The Control

There are two parameters that are controlled: **activation rate**: inactive mobiles do not contribute to communications in the DTN and do not use energy. By activating less/more mobiles per unit of time, one can use resources when needed; **transmission**: the beaconing transmission power is controlled in order to mitigate the battery discharge of active relay nodes.

In this paper we follow the fluid approximation which is shown to be tight for the sequence of encounter instants [13].

Fluid Approximations

Let $X(t)$ be the fraction of the mobile nodes that have at time t a copy of the message. Let $Y(t)$ denote the fraction of active mobiles at time t which do not have a copy of the message. $V(t)$ denotes the activation rate at time t and $U(t)$ denotes the transmission control. $X(t)$ grows at a rate given by the following pair of coupled differential equations:

$$\dot{X}(t) = U(t)Y(t)\xi \tag{1}$$

$$\dot{Y}(t) = -U(t)Y(t)(\xi+\mu) + V(t) \tag{2}$$

The term $U(t)Y(t)\xi$ above represents the increase in the number of mobiles with message copy. We also assume that $U(t) \in [u, 1]$ for some $u > 0$, and the activation rate V is bounded as $0 \le V(t) \le K(t), \quad 0 \le t \le T$, where $K(t)$ is a piecewise continuous function. Without loss of generality, we further assume that $\int_0^T V(t)dt = 1$.

Delivery Delay Distribution

The probability distribution of delay T_d, denoted by $\mathcal{D}(t) := P(T_d < t)$ is given by (see [14, Appendix A]),

$$\mathcal{D}(t) = 1 - (1-z)\exp\Big(-N\xi\int_{s=0}^{t} X(s)ds\Big), \tag{3}$$

Note that because of monotonicity, maximizing $\mathcal{D}(t)$ is equivalent to maximizing $\int_{s=0}^{t} X(s)ds$.

Energy Consumption

The total energy consumed for transmission and reception of message copies during $[0, T]$ is $\epsilon(X(T)-X(0))$. Moreover, the beaconing power used at time t by active relays is proportional to $U(t)Y(t)\xi$ so that the energy expenditure in $[0, T]$ due to beaconing is $\mu\int_0^T U(s)Y(s)ds$, i.e., $\frac{\mu}{\xi}(X(T)-X(0))$. Hence, it follows that the total energy consumed in time T is $\mathcal{E}(T) = (\epsilon + \frac{\mu}{\xi})(X(T) - X(0))$.

B. The Optimization Problem

Our goal is to obtain *joint optimal* policies for the activation $V(t)$ and the transmission control $U(t)$ satisfying constraints introduced earlier, that solve

$$\max_{\{V(\cdot)\in\mathcal{V}, U(\cdot)\}} \mathcal{D}(T), \quad \text{s.t.} \quad X(T) \le x, X(0) = z\,, \tag{4}$$

where x and z ($x > z$) are specified. Recall that maximizing $\mathcal{D}(T)$ is equivalent to maximizing $\int_0^T X(t)dt$.

III. Optimal Control

The solution to the problem will be shown to consist of policies involving two thresholds, one beyond which we stop activating mobile terminals, and the other beyond which we stop transmitting beacons. Earlier approaches based on Pontryagin's maximum principle (PMP) [6], based on sample path comparision [10] are not applicable due to their scalar nature. Accordingly, we develop a new approach that establishes the optimality of a threshold type policy for the activation control, following which we use PMP.

To obtain the optimal solution we first hold $U(t) \in [u, 1]$ fixed, carry out optimization with respect to $V(\cdot)$, and then we substitute the optimal $V(\cdot)$, $V^*(\cdot)$, back into the objective function and carry out a further maximization with respect to $U\cdot)$. For the first step, it is convenient to write the integral of $X(\cdot)$ explicitly as a $V\cdot)$, which turns out to be linear :

$$\int_0^T X(t)dt = \xi \int_0^T m(t)V(t)dt\,, \tag{5}$$

where $m(\cdot)$ is some appropriate function, an expression for which is provided in the next subsection.

A. Optimal Activation Control

With $U(t) \in [u, 1]$ fixed, we now first justify the equivalence (5), with an explicit expression for $m(\cdot)$, and then show that $m(\cdot)$ is non-increasing. This will allow us to conclude that the optimum choice for $V(\cdot)$ is of threshold form.

Lemma 3.1: Equivalence in (5) holds, with the expression for $m(\cdot)$ given in the proof below.

Proof : To derive the equivalent form, we solve the coupled equations (1)-(2) in terms of $V(\cdot)$ and $U(\cdot)$, with zero initial conditions. Further, using appropriate substitutions and integration by parts, we obtain,

$$\begin{aligned} m(t) &= Z(T)\Phi(0,t) - Z(t)\Phi(0,t) \\ &\quad -TW(t)\Phi(0,t) + tW(t)\Phi(0,t). \end{aligned} \tag{6}$$

where substitutions used in (6) are:

$$\begin{aligned} \Phi(t,T) &= \exp\left(-(\xi+\mu)\int_T^t U(s)ds\right), \\ dW &= U(\sigma)\Phi(\sigma,0)d\sigma, \quad dZ = dtW(t). \end{aligned}$$

$\diamondsuit$

Lemma 3.2: $m(t)$ is non-increasing in t for all $U(\cdot) \geq 0$, and is monotonically decreasing for $U(t) > 0$. Moreover, the expression for $m(\cdot)$ can equivalently be written from (6) as,

$$m(t) = \int_t^T (T-s)U(s)\Phi(s,0)ds\Phi(0,t) \tag{7}$$

Let us define

$$\ell := \inf\left\{t \in (0,T] : \int_0^t K(s)ds = 1\right\}. \tag{8}$$

Lemma 3.1 and Lemma 3.2 facilitates for the following.

Theorem 3.1: The optimal policy V^* exists and is given by

$$V^*(t) = \begin{cases} K(t) & \text{if } 0 \leq t \leq \ell, \\ 0 & \text{otherwise} \end{cases}. \tag{9}$$

Henceforth, we will assume that $V(s)$, seen as a measure, is non-degenerate, i.e., when it is applied at time t, nodes are active with positive probability from t onwards. Notice that $X(t)$ is a non-decreasing function for all $t > 0$, and monotone increasing function when $U(t)$ is strictly positive.

B. Optimal Transmission Control

We now proceed to derive the optimal transmission policy. Recall that $X(t)$ is a monotonic increasing function. Furthermore we notice that similarly to what was shown in [6], the controlled dynamics X with $U(t)$ can be interpreted as a slower version of the *uncontrolled* dynamics of X, i.e., the dynamics obtained when $U(t) = 1$. In this subsection, we first derive the uncontrolled dynamics for a general activation policy. This will then enable us to derive the optimal control policy in closed form.

1) Uncontrolled Dynamics: Let $\overline{X}(t)$ denote the *uncontrolled dynamics* of the system: it is the fraction of infected mobiles when $U(t) = 1$ for $0 \leq t \leq T$.

Proposition 3.1: For a given activation policy V, the fraction of infected nodes under $U(t) = 1$ and $X(0) = z$ is

$$\overline{X}(t) = \frac{\xi}{\xi+\mu}\int_0^t (1 - e^{-(\xi+\mu)(t-s)})V(s)ds + z \tag{10}$$

Proof : From (1) and (2) we have

$$\begin{aligned} \dot{X}(t) + \frac{\xi}{\xi+\mu}\dot{Y}(t) &= \frac{\xi}{\xi+\mu}V(t) \\ \Rightarrow Y(t) &= (f(t) - X(t))\frac{\xi+\mu}{\xi} \end{aligned} \tag{11}$$

where we introduced $f(t) := \frac{\xi}{\xi+\mu}\int_0^t V(s)ds + z$, which depends only on the activation control. The uncontrolled version $\overline{X}(t)$ is obtained by substituting (11) in (1) for $U(t) = 1$, which leads to: $\dot{\overline{X}} + (\xi+\mu)\overline{X} = (\xi+\mu)f$. The solution is :

$$\overline{X}(t) = e^{-(\xi+\mu)t}\int_0^t e^{(\xi+\mu)s}\xi\int_0^s V(r)drds + z. \tag{12}$$

Further, by integration by parts we obtain (10). $\diamondsuit$

Remark 3.1: For any given activation policy V, we substitute (11) into (1) to obtain a single differential equation, which is equivalent to the original system (1)-(2), i.e.,

$$\dot{X} = U(t)\xi g(X,t) \tag{13}$$

where $g(X,t) := (f(t) - X(t))\frac{\xi+\mu}{\xi}$.

We observe also that in case $U(t) = c, t \in [0,T], u \leq c \leq 1$ is a constant energy control policy, a simple time-rescaling argument offers

$$X(t) = \frac{\xi}{\xi+\mu}\int_0^t (1 - e^{-c(\xi+\mu)(t-s)})V(s)ds + z = \overline{X}(ct). \tag{14}$$

In the following using the uncontrolled dynamics of the system, we can obtain an explicit form of the optimal transmission control using the maximum principle [15].

2) Optimal Control:

Definition 3.1: A policy U restricted to take values in $[u, 1]$ is called a threshold policy with parameter h if $U(t) = 1$ for $t \le h$ a.e. and $U(t) = u$ for $t > h$ a.e..

Theorem 3.2: Consider the problem of maximizing $\mathcal{D}(T)$ with respect to $U(\cdot)$ subject to the constraint $X(T) \le z + x$, under the activation control V.

i. If $\overline{X}(T) \le x + z$, then the optimal policy is $U(t) = 1$.
ii. If $\overline{X}(uT) > x + z$, then there is no feasible solution.
iii. If $\overline{X}(T) > x+z > \overline{X}(uT)$, then there exists a threshold policy. An optimal policy is necessarily a threshold one in the form

$$U^*(t) = \begin{cases} 1 & \text{if } t \le h^* \\ u & \text{if } t > h^* \end{cases} \quad (15)$$

IV. Joint Optimal Control

The analyses above have clearly led to the complete solution of the optimization problem (4), which is captured below.

Theorem 4.1: For the optimization problem (4), the solution is given by the optimal activation control $V^*(t)$ applied jointly with the corresponding threshold policy (as optimal transmission control) given in Thm. 3.2.

A. Activation and Transmission Thresholds

We have seen that the optimal policies are characterized by two scalar quantities, ℓ and h^*, taking values in $(0, T)$. One interesting question now is whether one should wait for all the nodes to be activated before switching off the transmission control or not, i.e., whether it should be $h^* \le \ell$ or $h^* > \ell$. If $h^* \le \ell$, it is then possible to activate a smaller number of relays with consequent energy savings; thus it is of interest to know the relative order of the thresholds h^* and ℓ.

Let us introduce $\underline{X}$ as the optimal dynamics for $t \ge h^*$: from (1)-(2) and fixing the control $U(t) = u$ for $t \in [h^*, T]$, with initial condition $X(0) = \overline{X}(h)$, we have

$$\dot{\underline{X}}(t) + u(\xi + \mu)\underline{X}(t) = u(\xi + \mu)f$$

Hence, the optimal dynamics for $t \ge h^*$ is of the form

$$\begin{aligned} \underline{X}(t) &= e^{-u(\xi+\mu)(t-h)} \int_0^t e^{u(\xi+\mu)s}(\xi + \mu)uf(s + h)ds \\ &\quad + \overline{X}(h)e^{-(\xi+\mu)(t-h)}, \quad t > h. \end{aligned}$$

Notice that $X(T) = \underline{X}(T) = x$. Without loss of generality we assume henceforth $z = 0$.

Theorem 4.2: If $T > \max\{h^*, \ell\}$, then the following relation holds for the bound x and the threshold h^*:

$$\begin{aligned} &h^* > \ell, \quad \text{if } x > \overline{X}(\ell) + \Delta X(\ell, T), \\ &h^* \le \ell, \quad \text{otherwise}, \end{aligned} \quad (16)$$

where
$$\begin{aligned} \overline{X}(\ell) &= \frac{\xi}{\xi + \mu} \int_0^\ell (1 - e^{-(\xi+\mu)(\ell-s)})V(s)ds, \\ \Delta X(\ell, T) &= \left(\frac{\xi}{\xi + \mu} - \overline{X}(\ell)\right)\left(1 - e^{-u(\xi+\mu)(T-\ell)}\right). \end{aligned}$$

$\overline{X}(\ell)$ denotes the uncontrolled growth of X in $t = (0, \ell]$ and $\Delta X(\ell, T)$ refers to the increment in X in $(\ell, T]$ under the controlled dynamics (with $U = u$). Moreover, when both threshold times coincide, i.e. $h^* = \ell$, the bound x can be expressed as

$$x = X(T) = \overline{X}(\ell) + \frac{\xi}{\xi + \mu}(1 - e^{-u(\xi+\mu)(T-\ell)}).$$

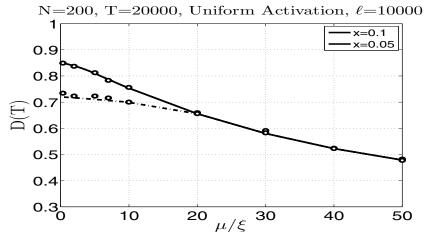

Fig. 1. Success probability for increasing values of μ/ξ, under uniform activation with $\ell = 10000$ s and $x + z = 0.05, 0.1$, respectively.

In [12], we characterize the following activation policy: i) Uniform activation: $K(s) = K_0$; ii) Linear activation: $K_0 = 2/\ell^2$, and iii) Exponential activation: $K_0 = \alpha/(\exp(\alpha\ell) - 1)$. In a scenario such as energy harvesting, it is expected to have cyclic kind of activation, e.g. more nodes are activated during the day exploiting solar energy than are at night. *Uniform activation* can be used to study such processes [12].

B. Impact of time horizon T

In the earlier sections we showed that optimal transmission control policy U^* is a threshold policy for finite (fixed) time horizon and state-constrained problem. We now consider the case as T goes to infinity, and analyze asymptotically the impact on optimal policies.

Optimal activation policy V^* derived in the previous section clearly indicates that early activation is optimal (satisfying the rate constraint $K(t)$). We also saw that V^* is the same for T above some value ℓ. We next study the impact of T on U^*. This is summarized in the proposition below. Define $\underline{T}_m := sup\{t : \underline{X}(t) \le x\}$ and $\overline{T}_m := sup\{t : \overline{X}(t) \le x\}$.

Proposition 4.1: Consider maximization of $\mathcal{D}(T)$ subject to the constraint $X(T) \le z + x$, under the optimal activation control V^* and transmission control $U(t) \in [u, 1]$.

i. For $u > 0$, there is no feasible policy for any $T > \underline{T}_m$.
ii. For $u = 0$, the optimal transmission policy when $T \to \infty$ is given by,

$$A^* = \begin{cases} U(t) = 1 & \text{if } t \le \overline{T}_m \\ U(t) = 0 & \text{if } t > \overline{T}_m. \end{cases} \quad (17)$$

V. Numerical Validation

Here we provide a numerical validation of the model. Our experiments are trace based: message delivery is simulated by a Matlab script receiving as input pre-recorded contact traces; in our simulations, we assume time is counted from the time when the source meets the first node, so that $z = 1 + P_a$, where P_a is the probability that the first node met is active. Also, active nodes lifetime is an exponential random variable with parameter μ.

We considered a Random Waypoint (RWP) mobility model [13]. We registered contact traces using Omnet++ in a scenario where N nodes move on a square playground of side 5 Km. The communication range is $R = 15$ m, the mobile speed is

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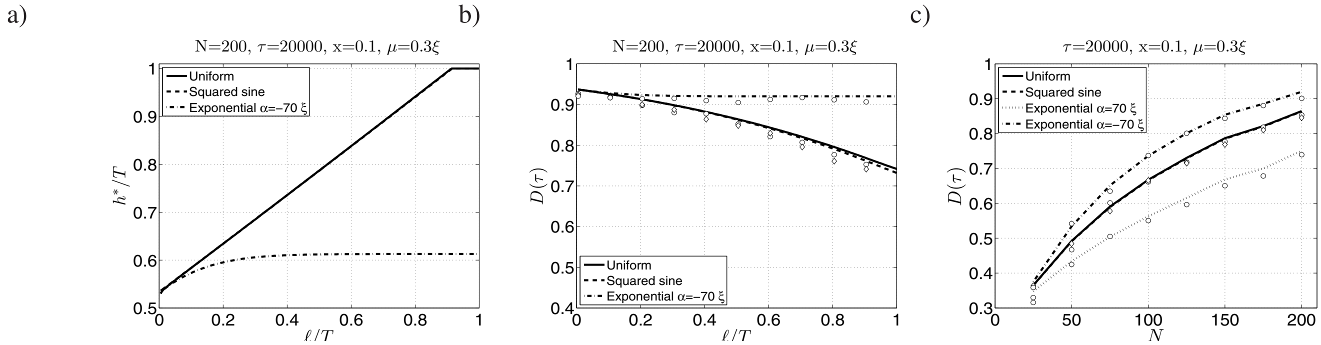

Fig. 2. a) Optimal threshold as a function of ℓ b) Corresponding success probability $\mathcal{D}(T)$ c) Success probability for increasing number of nodes. Different lines refer to the case of uniform (solid), squared sine and truncated exponential activation bounds

$v = 4.2$ m/s and the system starts in steady-state conditions in order to avoid transient effects [16].

The time limit is set to $T = 20,000$ s. Most graphs refer to the case $N = 200$. We first show the effect of μ on the success probability $\mathcal{D}(T)$. Fig. 1 depicts the success probability for increasing values of μ. As expected, the higher the relative magnitude of μ with respect to ξ, the lower the success probability. However, the effect of energy exhaustion due to beaconing takes over for larger values of μ and causes a much faster decay in case of looser constraints on energy ($x + z = 0.1$) than in the case of tighter ones ($x + z = 0.05$).

Also, we compared the effect of the activation bound on the success probability $\mathcal{D}(T)$. In particular, we considered three alternative bounds: uniform, squared sine and exponential. In the case of a squared sine bound, we let $K(t) = \frac{2}{\ell}\sin^2(\frac{2}{\pi}\frac{t}{\ell})$. The comparison with the uniform activation shows that they result in a similar performance: as observed in Fig. 2a) the optimal transmission control and as a consequence the success probability (Fig. 2b)) as a function of ℓ is similar. This behavior is due to the fact that in both cases $h^* \geq \ell$ and the two activation measures have the same expected value [12] (the system loses memory of the shape of the distribution as soon $h^* \geq \ell$). We also depicted the behavior in the case of a bound given by a truncated exponential where $\alpha = -70\xi$: as seen in Fig. 2a) and Fig. 2b), the higher activation rate permits a larger success probability. This effect becomes dominant at larger values of ℓ and this results in the slower increase of the transmission threshold which saturates to a reference value.We repeated the measurements on the success probability $\mathcal{D}(T)$ for increasing numbers of nodes, as reported in Fig. 2c). We can see the match of the uniform activation and the squared sine one. Also, we reported the behavior under truncated exponential activation in the case of $|\alpha| = 70\xi$; the success probability in all these examples is seen to depend mostly on the expected value of V^*, as observed earlier.

VI. Concluding Remarks

In this work, we have considered the joint optimization problem underlying activation of mobiles and transmission control in the context of DTNs. Multi-dimensional ordinary differential equations have been used to describe (using the fluid limit) the associated system dynamics. Since the previously used approaches were not applicable to establish the structure of optimal activation policies, we devised a new method that is based on identifying the exact weight of the activation control at each time instant. We further validated our theoretical results through simulations for various activation schemes or constraints on activation.

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